Conditional Random Fields

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Sums of logs

Issue: computing α forward probabilities can undeflow

- Normally we'd fix this using logs
- But α requires a sum of probabilities
  - Not easy to do in log-space

Solution 1: scale/exponentiate

```
def logplus(xx, yy):
    M = max(xx, yy)
    return M + log(exp(xx - M) + exp(yy - M))
```

Because:

- Subtracting M in logspace is equivalent to dividing
- So we have $\frac{x}{M} + \frac{y}{M}$ (one of these is 1)
  - Doesn't underflow
- Computes $\frac{1}{M}(x + y)$
- Then take the log again, and multiply by M to get $log(x + y)$

Solution 2

Normalize the α values at each timestep.

- At a single timestep, we'd get:

$$A(i) = \sum_t \alpha_t(i) = P(W_{1:i})$$

- Divide all the $\alpha_t(i)$ by $A(i)$

$$\alpha'_t(i) = \frac{\alpha_t(i)}{A(i)} = P(T_i = t | W_{1:i})$$

Now the α' are not so small (since they have to sum to 1).
Applying this recursively, we get that:

$$A'(i) = \sum_t \alpha'_t(i) = P(W_i)$$

We can extract the probability of all the words:

$$\log P(W_{1:n}) = \log \prod_i A'(i) = \sum_i \log A'(i)$$

Conditional random fields

- A model which handles sequences
  - Like the HMM
- And can use many correlated features
  - Like the max-entropy classifier
- By combining the two ideas

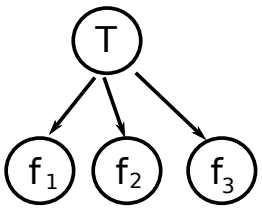
Text here: Sutton and McCallum “An introduction to conditional random fields”

- Has everything you want to know
- Relatively accessible
- Really, really long
  - Basics: sections 2.2-2.4
  - Applications: 2.5-2.7
  - Algorithms: 4.1, 4.3, 5.1

Review: generative vs conditional

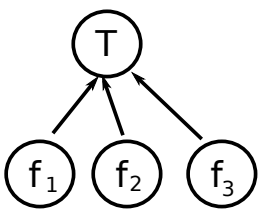
Generative model

- Model of the observed data (features F, tag T)
- Params maximize $P(F, T; \theta)$
  - The joint probability of all observations



Conditional model

- Model of the tag as a function of the data
- Params maximize $P(T|F; \theta)$
  - The probability of the tag



Deriving the conditional model

- Move away from having a *probability* over feature values
- Instead have *weights* for feature values
- Want to optimize using gradient (calculus)
  - Because weights are correlated so estimation isn't obvious
- Easier to take derivatives if everything is a sum
- So: use exp log to transform products into sums
- End up with dot product

Making an HMM into a dot product

$$
\begin{aligned}
P(T_{1:n}|W_{1:n}) &= \frac{\prod_{i=0}^{n} P_{trans}(T_{i+1}|T_i) P_{emit}(W_i|T_i)}{P(W_{1:n})} \\
&= \frac{\exp \log \prod_{i=0}^{n} P_{trans}(T_{i+1}|T_i) P_{emit}(W_i|T_i)}{P(W_{1:n})} \\
&= \frac{\exp \left(\sum_{i=0}^{n} \log P_{trans}(T_{i+1}|T_i) \log P_{emit}(W_i|T_i) \right)}{P(W_{1:n})}
\end{aligned}
$$

- Let $f_{t \to t'}(T) = (T_{i+1} = t', T_i = t)$ and $\theta_{t \to t'} = \log P(t'|t)$
- Let $f_{t \to w}(T) = (T_i = t, W_i = w)$ and $\theta_{t \to w} = \log P(w|t)$
- Defines a feature vector $F(T)$ (specific to tags T)

$$
= \frac{\exp(\Theta \cdot F(T))}{P(W_{1:n})}
$$

Making it conditional

$$P(T|W) = \frac{\exp(\Theta \cdot F(T))}{P(W_{1:n})}$$
$$= \frac{\exp(\Theta \cdot F(T))}{\sum_{T'_{1:n}} \exp(\Theta \cdot F(T'))}$$

To make this conditional:

- Drop constraint that θ are log probabilities
- Choose θ to maximize probability of training $P(T|W)$
- Normalizer is no longer interpretable as $P(W_{1:n})$

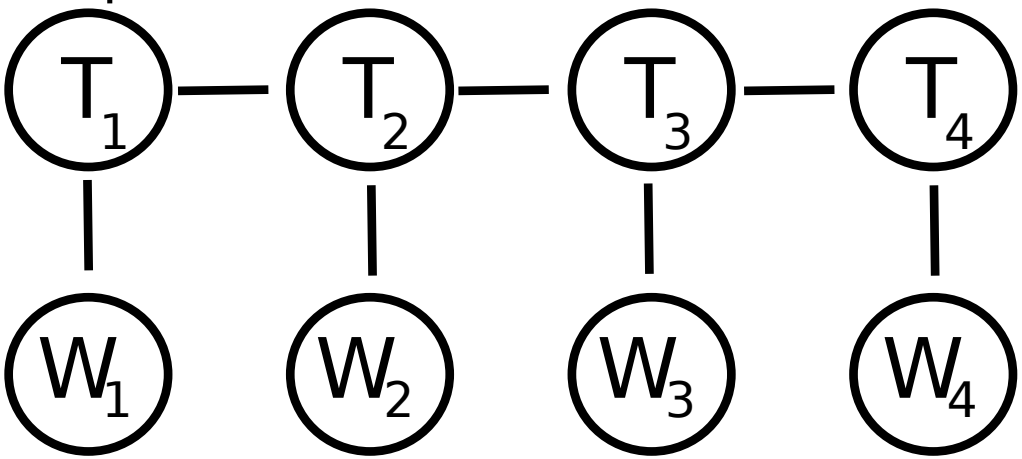
$$Z(\Theta) \text{ or } Z = \sum_{T'_{1:n}} \exp(\Theta \cdot F(T'))$$

- The “normalizing constant” or “partition function”
- Notation Z and partition name from statistical physics

(Linear-chain) CRF

$$P(T|W) = \frac{1}{Z} \exp(\Theta \cdot F(T))$$

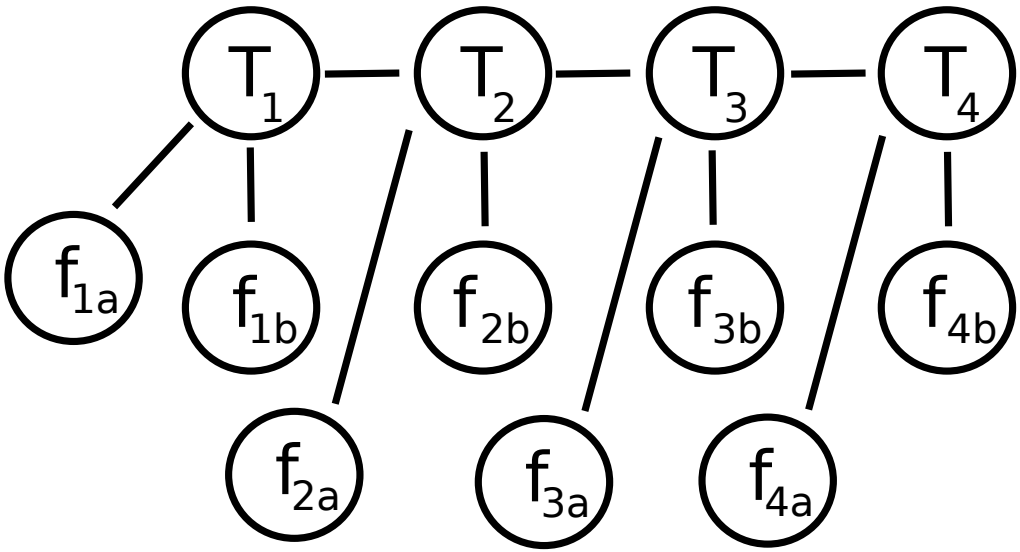
Graphical model:



Undirected graphical model

- No arrows
- Arcs in the graph represent weights
- No interpretation of arc as conditional prob...
- Just a number that gets multiplied!

Adding features



- We can add features of the word just like in max-entropy
- Capitalization, numeric, suffix, etc

Inference

What we want:

$$\max P(T_{1:n}|W_{1:n}) \propto \exp \Theta \cdot F(T)$$

We can simply maximize the weight $\Theta \cdot F(T)$

- This breaks down into a sum of the f features and θ weights
- Can maximize with Viterbi
- Write initial weight of 0 under <s>
- On an arc, add transition and emission θ

$$\mu_t(i) = \max_{t'} \theta_{t \to w} + \theta_{t' \to t} + \mu_{t'}(i-1)$$

Estimation

Using gradient:

- As in max-entropy model, gradient is difference of:
  - Count of feature f in true labelings (from numerator)
  - Expected count of feature f (from denominator)
- Numerator term is easy (just count!)
- Denominator term is harder

$$E_{P(\theta)}[f_{t' \to t}(T)] = \sum_{T', W \in D} P(T'|W;\Theta)\#(f_{t' \to t}(T))$$

Sum over all *possible* tag sequences of probability times whether feature is active

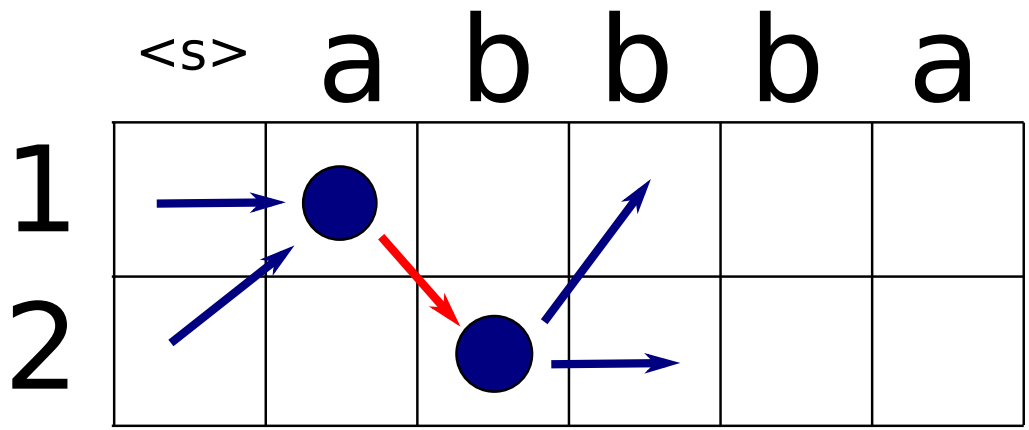
- Can compute using forward-backward

Forward-backward for CRF

Want to compute:

$$\sum_{T', W \in D} P(T' | W; \Theta) \#(f_{t' \to t}(T))$$

Basic question: probability that $f_{t' \to t}$ is active at time i



Very similar to tag marginals!

$$P(T_i = t', T_{i+1} = t) \propto \alpha_{t'}(i) \theta_{t' \to t} \theta_{t \to w_{i+1}} \beta_t(i+1)$$

Feature design

Consequence: we can compute gradient easily for:

- Features which look at a single $T_i \in T_{1:n}$
  - And *any* words W (since they don't depend on T)
- Features which look at T_i, T_{i+1}
  - And *any* words W

Hard(er) to compute for:

- Features which look at more than two tags
- Features for non-adjacent tags
- These require altering the dynamic program somehow

Features which only look at W and not T don't do anything:

- Since we only care about $P(T|W)$

CRF training can be slow

- To compute the gradient, we have to run forward-backward
- CRF training can be as slow as your HMM program *times* your max-ent program
- Using someone else's software highly recommended

CRFSuite

Recommended software for the project:

- Like Megam, you transform your data into a feature file
- It learns the weights

Data format:

```
LABEL FEAT FEAT ...
LABEL FEAT FEAT ...
                          <----- end of sentence
LABEL FEAT FEAT ...
```

CRFSuite automatically computes θ values for:

- All $\theta_{t' \to t}$ (based on the labels you use)
- All $\theta_{t \to f}$ (based on the features you use)
- No way to specify other feature types such as t', t, w in this software

Using CRFs as chunkers

Typical problem: find and label subsequences of text:

Named entity recognition

Pick out all strings referring to specific individual in the world

- Identify entity type (person/organization/place/date...)

"[$_{PERS}$ Mary] works for [$_{ORG}$ The Ohio State University]"

Sequence labeling:

- Because labeling of name words affected by context
- "[$_{PLACE}$ Ohio]", and "a university"

Standard problem setup

- Four tags per NE label
- *BEGIN-ORG*, *IN-ORG*, *LAST-ORG*, *UNIT-ORG* (one word)
- And neutral *OUTSIDE* tag

"Students *OUT* at *OUT* Ohio *BEGIN-ORG* State *IN-ORG* University *LAST-ORG* are *OUT* studying *OUT*"
"Students *OUT* at *OUT* OSU *UNIT-ORG* are *OUT* studying *OUT*"
(Sometimes called *BILOU* coding)

- Could just use *ORG* and *OUT*, but not as good

Relation extraction

"Extracting Relation Descriptors with Conditional Random Fields", Li, Jiang, Chieu, Chai 2011
Task: extract entity pairs that have some relationship

- Employment: "said ARG-1, a vice president at ARG-2"
- Personal: "ARG-1 later married ARG-2"

Basic solution: treat as sequence labeling with tags *ARG-1-EMPLOYMENT*, *ARG-2-EMPLOYMENT*, *ARG-1-PERSONAL* etc

- Using BILOU-like coding scheme

Issues

Task has long-distance dependencies (only one ARG-1 and ARG-2 per relation per sentence, etc)

- Markov property violated
- Modify dynamic program by adding some long-distance features
  - Exponential slowdown, but this is research, I guess
- Sequence of words between *ARG* tags
- Standard CRF scores 73% F-score
- Modified CRF up to 80%
- No timing figures in paper...

Hindi NER

"Rapid Development of Hindi Named Entity Recognition using Conditional Random Fields and Feature Induction", Li and McCallum 2003
Find all PERSON, LOCATION, ORGANIZATION in Hindi news:

- Throw in word, characters from word, prefix/suffix, lists of Hindi NEs
- Use stepwise feature selection procedure
  - Add batch of features
  - Calculate approximate gain in LL from each one
  - Keep the good ones
  - Repeat
- Search over features, conjunctions of features

$\sim$70% F-score

Transliterating Chinese

"Forward-backward Machine Transliteration between English and Chinese Based on Combined CRFs", Qin and Chen 2011 Workshop on Named Entities

Use two CRFs:

- First to find "chunks" of characters that represent a sound
  - BILOU-like encoding
- Second to label each chunk with some foreign characters

Results aren't great:

- En->Zh: ∼70% characters correct
- Zh->En: ∼76% characters correct
- Whole name about 30% of the time